Supplemental material

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Appendix 1: protocol for systematic review

Administrative information

Title:

Systematic review of prognostic models for predicting falls in community-dwelling older adults

Registration:

This protocol was registered with the International Prospective Register of Systematic Reviews (PROSPERO) on (1st February 2019).

Registration number: CRD42019124021

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Contributions:
GS is the guarantor. GS drafted the manuscript for the protocol and performed preliminary searches and search strategy. GS, JR, MGJ and SA developed selection criteria. JRI will assist GS in screening titles, abstracts and reference lists of papers included after full-text reading along with data extraction, assessing risk of bias, presence of meta-bias along with adherence to reporting guidelines. KT will assist GS in full-text reading. MGJ will be arbitrator if agreement cannot be reached between reviewers. GS will draft the manuscript for the paper. MGJ, JRY, SA, TM, JRI and KT will assist in interpretation of results, read, provide feedback and approve the final manuscript of the paper.

Amendments:
In the event of protocol amendments, this section will describe the date, changes and rationale of each amendment. Changes will be incorporated into the protocol sections. All authors will be responsible for approving the amendments. Also, GS will be responsible for documentation and implementation of these.
Current version of the protocol: 3.

- 7th of August 2019
    - **Change #1:**
        - Setting:

- We further specified which setting the review is, and is not, intended for. We changed the wording "community setting" to "general population setting". Also, we specified that prediction models intended for a primary care would also be excluded.

  - Rationale:
    - Change in wording: To apply the same terminology of the CHARMS checklist.
    - Primary care exclusion: To increase transparency and homogeneity in settings.

- **Change #2:**
  - Risk of bias:
    - As a supplement to the risk of bias assessments, the newly published TRIPOD adherence tool will be used.
  - Rationale
    - To assess adherence to reporting guidelines for prediction modelling studies.

- 17th of June 2019
  - **Change #1**
    - Study design:
      - We further specified which study designs would not be included. Thus, randomised controlled trials and retrospective cohort studies will not be included.
    - Rationale:
      - To increase transparency.
  - **Change #2:**
    - Participants: Age
      - We further specified the inclusion criterium regarding age. Thus, studies with total age ranges extending below 60 years will be excluded. Exclusion will also be made if mean age subtracted by two standard deviations extends below 60 years of age unless inclusion criterium in studies specifically states a lower age limit of 60 years or above.

- Rationale:
  - To increase transparency.

- **Change #3:**
  - Participants: Community-dwelling
    - We further specified which studies would be included. Thus, we will include studies excluding certain types of community-dwelling individuals, e.g. with known neurological, spinal or cognitive disorders.
  - Rationale:
    - These samples may also contribute with relevant information about the target population.
- **Change #4:**
  - Index (Model):
    - We further specified which studies to include based on the model presented. Thus, we will also include studies with:
      - Two or more prognostic factors combined into a scale giving an individual score used to assess the predictive performance on future falls.
      - Two or more prognostic factors included in a test instrument from which a prediction model would be generated.
  - Rationale:
    - To increase transparency.
- **Change #5:**
  - Outcome (and rationale):
    - We further specified which studies to include based on the outcome. Thus, studies without an outcome definition will also be included since this will not rule out the outcome definition of this review. We will exclude studies using falls definitions excluding certain types of falls presumed to be due to a specific cause e.g. acute medical events or external forces. This post fall classification method may introduce assessor-bias.

Gade GV, *et al. BMJ Open* 2021; 11:e044170. doi: 10.1136/bmjopen-2020-044170

Support:
The Department of Geriatric Medicine, Aalborg University Hospital, Aalborg, Denmark and the Department of Clinical Medicine, Aalborg University, Aalborg, Denmark will fund and sponsor this research.

Introduction:

Rationale of the review

Falling over in community-dwelling older adults is a frequent problem with an annual prevalence of 30 % in 65+ year olds and 50 % in 80+ year olds.[1] Total number of falls are expected to increase significantly in the future due to the ageing population.[2,3] For instance, in 2017, the global population of 65+ year olds was estimated to be 962 million and is estimated to increase towards 1.4 and 2.1 billion in 2030 and 2050 respectively.[2] This frequent and escalating problem of fall accidents is a major concern globally due to their associations with elevated morbidity, mortality, poorer physical functioning and early admission to long-term care facilities which leads to elevated financial costs to society[4–6].

Fall prevention is therefore highly relevant to society, next of kin and to the individual. Unfortunately, more than 400 risk factors for falling have been identified thereby making it a complex area/problem.[7] In addition, the risk factors spread across different domains including socio-demographics, the environment, medical conditions and medications, physical performance, psychology and cognition[8]. In consequence, secondary multifactorial fall risk prevention has been recommended[3,9]. On the other hand, if individuals at high risk of falling could be identified before their first fall, primary preventive interventions could be instituted, which would be even more beneficial. Therefore, individual assessments of fall risk using multifactorial prognostic prediction models are imperative. Few reviews on the ability of prognostic prediction model studies to discriminate fallers from non-fallers in community-dwelling older adults exist[10–12]. However, in these reviews, methodologies were varied with no review protocols being reported[10–12], outcome definitions not following the current consensus definition[10–13], and search strategies being restricted[10,12] or based on search filters for diagnostic studies[11,12]. Also, risk-of-bias assessments were done using tools designed for diagnostic studies[11,12] and reporting of data extraction items and -methods were inconsistent[10,12].

Nonetheless, in recent years, prognostic research methods have evolved. Thus, new guidelines have been published to encourage researchers to transparently report prediction modelling studies[14], systematic reviews[15] and their respective protocols[16]. Also, within the field of prediction modelling reviews, literature search strategies[17] along with guidance papers on data extraction items[18] and risk

of bias tools[19] have been developed. However, no reviews on fall prediction studies have applied the abovementioned guidelines as yet.

The scope of this review is to provide a systematic update on current model performance, and other characteristics, on developmental and validation studies within the field of fall accidents on multifactorial prognostic prediction models in community-dwelling older adults.

Objective:

The aim of this systematic review is to describe model performance along with other model characteristics (predictors along with methods of model development, -evaluation and -presentation) of existing multifactorial prognostic prediction models on falls in 60+ year old non-institutionalised, community-dwelling older adults.

Methods:

This protocol follows the guidelines of the Preferred Reporting Items for Systematic reviews and Meta-analyses Protocols (PRISMA-P)[16]. The protocol is registered in the PROSPERO database.

Eligibility Criteria

The following criteria outlined below will be used to select studies for the review.

Study designs:

We will only include prospective cohort studies since this is the preferred design for prognostic prediction modelling studies[14]. We will include both developmental and validation studies with and without model updating. Randomised controlled trials will not be included since these tend to have narrow predictor distributions resulting in poor discriminatory performance. This may also be influenced by treatment effects in the design[18]. Furthermore, generalisation to the target population may be compromised due to strict eligibility criteria[20]. Retrospective cohort studies will be excluded since the predictive performance may be substantially limited by missing data, and only predictors available in the data set collected can be applied[18].

Participants:

Only studies with all participants aged 60 years or older will be included. This cut-off was chosen in order to encompass studies using different age cut-offs for being an older adult. Thus, studies with total age ranges extending below 60 years will be excluded. Also, mean age subtracted by 2 standard deviations must not extend below 60 years unless inclusion criteria specifically stated a lower age limit of 60 years or above.

Participants should be community-dwelling and not institutionalised, i.e. living independently and not in nursing homes or short term-care where the risk of falling is substantially different from

the general population[21]. Studies restricted to participants with pre-specified diseases, conditions or symptoms such as Parkinsonism or stroke will be excluded so that generalisation to the overall community population is not compromised. We will include studies excluding certain types of community-dwelling individuals, e.g. with known neurological, spinal or cognitive disorders since these samples may contribute with relevant information about the target population of the review.

Index (Model):

Multifactorial prognostic prediction models, i.e. including 2 prognostic factors or more due the multifactorial aetiology of falls[3,22]. Thus, explanatory studies investigating the association between a predictor and prospective falls were excluded. To broaden the search, we will include the following studies with:

- Two or more prognostic factors measuring on the same domain will be included.
- Two or more prognostic factors combined into a scale giving an individual score used to assess the predictive performance on future falls.
- Two or more prognostic factors included in a test instrument from which a prediction model would be generated.

Comparator:

None.

Outcome:

Primary outcome in the included prospective cohort studies will be falls defined by "an unexpected event in which the participants come to rest on the ground, floor, or lower level".[13] Both single and recurrent falls, i.e. >1 fall, will be included. Studies without an outcome definition were also included since this would not rule out the abovementioned definition. We excluded studies using falls definitions excluding certain types of falls presumed to be due to a specific cause e.g. acute medical events or external forces. This post fall classification method may introduce bias in the outcome assessment due to the subjective judgements involved[23].

Timing:

No restrictions on follow-up on falls will be made.

Setting:

The models should be used to screen for risk of prospective falls in a general population setting, and we will exclude models intended for primary care, hospitals and nursing homes.

Language:

Only studies reported in an English, Danish, Norwegian or Swedish language will be included. This was chosen due to resource limitations. However, a list of possibly relevant studies in other languages found during the literature search will be included in an appendix.

Publication year:

No restrictions on publication year will be made.

Information sources

Studies will be collected from the following databases: Pubmed.gov (PubMed interface, inception date to date of search), EMBASE (Embase.com, inception date to date of search), CINAHL (EBSCOhost interface, inception date to date of search), The Cochrane Library (Wiley interface, inception date to date of search), PsycINFO (APA PsycNET interface, inception date to date of search) and Web of Science (Web of Science Core Collection, inception date to date of search). Both controlled terms (i.e. MeSH or EMTREE terms) and simple phrase terms will be used to search the databases when appropriate. Also, hand searches from the reference lists of the included studies will be performed. Conference abstracts found during the literature search will only be used for obtaining their respective full-text articles. If not found elsewhere, we will try to contact the respective authors for this. If the full-text articles are not obtainable, the study will be excluded. However, a list of these possibly relevant studies found during the literature search will be included in an appendix. Primary literature within prior systematic reviews on fall prediction models found during the literature search will be screened. Finally, two experts in the field of falls research will be consulted to enquire for knowledge on additional studies fulfilling the eligibility criteria of this systematic review.

Grey literature

PROSPERO will be searched for completed reviews with this focus. Also, Clinicaltrials.gov, WHO International Clinical Trials Registry Platform, Open Grey, GIN, NICE, CRD/HTA, SIGN will be searched for relevant studies using key-terms from the main search (falling AND elderly OR Older adults). If not found elsewhere, we will try to contact authors of these relevant studies for retrieving of the full-text.

Search strategy

The search strategy follows current Cochrane recommendations for systematic reviews on prediction models[17,24]. Also, to accommodate the search strategy to our eligibility criteria, the search string was further developed by GS in collaboration with a Health Sciences Librarian at the Medical Library of Aalborg University Hospital, Denmark. The search strategies of the selected databases are included in Appendix 1. The final search strategy will be approved by a second reviewer (KT).

Study records:

Data management:

Duplicates will be removed using EndNote (EndNote X9, Clarivate Analytics, Philadelphia, USA). The results of the literature search will be uploaded to Covidence (Covidence systematic review software, Veritas Health Innovation, Melbourne, Australia. Available at www.covidence.org) to ease the collaboration between reviewers on titles and abstracts screening along with full-text reading. Risk of bias assessments and extraction of data will be performed using a standardised form in REDCap using a double data-entry module[25]. If several articles report results from the same trial, the "primary publication" will be prioritized; i.e. typically defined as the first full-text publication reporting on the primary outcome.

Selection process:

Screening titles and abstracts:

Two reviewers (GS and JRI) will independently screen titles and abstracts from the inclusion criteria. The screening process of titles and abstracts will undergo pilot testing. Reviewers (GS and JRI) will meet and discuss the inclusion of the first 50 articles found by the search strategy during screening of titles and abstracts. If agreement cannot be reached, a third author (MGJ) will be consulted for arbitration. If needed afterwards, refinement of inclusion criteria will be performed.

Full-text reading

Full-text reports will be obtained on eligible studies, and studies where uncertainty exists regarding eligibility based on titles and abstracts. GS and KT will independently screen the full-text reports for a final decision on eligibility. Disagreement among the reviewers will be discussed. If agreement cannot be reached, a third author (MGJ) will be consulted for arbitration. Reasons for excluding studies after full-text reading will be provided.

Data collection process:

Two reviewers (GS and JRI) will independently extract data from a pre-specified form (see Data items) in REDCap from each study found eligible for inclusion after full-text reading. If data reporting is incomplete, we will try to contact authors of the relevant studies to obtain data. A maximum of two attempts will be done to contact the authors by e-mail. If e-mails are not responded within 1 month from the first e-mail sent, the data field will be labelled as having no information. If the authors do not gain access to data, these will be extracted from figures and graphs if possible. If companion studies (multiple reports of the same study) with the same outcome of falls is found, data will be

extracted from the primary publication of the study. Disagreement among the reviewers will be discussed. If agreement cannot be reached, a third author (MGJ) will be consulted for arbitration. The total number of times arbitration by a third author was required will be given.

Data items:

Data extraction will comply with Critical Appraisal and Data Extraction for Systematic Reviews of Prediction Modelling Studies (CHARMS) guidelines.[18] The following data will be extracted if possible:

- General study information:
    - Authors.
    - Year of publication.
    - Study design.
    - Type of prediction modelling study:
        - Developmental without external validation.
        - Developmental with external validation.
        - External model validation without model updating.
        - External model validation with model updating.
        - Others
    - Country of origin.
    - Setting where candidate predictors were measured.
    - Number of study centres.
    - Inclusion criteria.
    - Exclusion criteria.
    - Sample size.
    - Methods for participant recruitment/sampling:
        - Consecutive sampling.
        - Convenience sampling.
        - Probability sampling.
        - Others
    - Dates of participant recruitment.
    - Duration of follow-up.
    - How many participants completed follow-up percentage-wise?
- Participants:

  - Gender.
  - Age.
  - Fall history.
- Outcome:
  - Outcome definition.
    - Was it pre-specified?
  - Type of fall recording/method of outcome measurement.
  - Was the same outcome definition and recording method used in all participants (Yes/No/Not Available)?
  - Was the outcome assessor blinded towards predictors (Yes/No/Not Available)?
  - Number of falls.
  - Number of fallers.
  - Number of non-fallers.
  - Number of frequent fallers.
  - Fall-rate per person per year.
  - Summary of follow-up period.
- Candidate predictors:
  - Number of candidate predictors studied.
  - Definitions of candidate predictors.
  - Methods for measuring candidate predictors.
  - Number of outcomes (falls) in relation to number of candidate predictors (events per variable (EPV)).
- Missing data:
  - Number of participants with missing data (both predictors and outcomes) in total.
  - Did participants with missing data differ from those without missing data (Yes/No/Not Available)?
  - Number of participants with missing data in total for each predictor
  - Method of handling missing data.
    - Single imputation
    - Multiple imputation
    - Participants with missing data were excluded from the analysis (complete case analysis)

        - Others (comment).
    - Were participants with missing data included in the model development, validation or updating (Yes/No/Not Available)?
- Model development (not relevant if the prediction modelling study does not include model development):
    - Type of model:
        - Linear regression
        - Logistic regression.
        - Survival analysis.
        - Others (comment).
    - Were assumptions for the model checked (Yes/No/Not available)?
    - Were assumptions for the model satisfied (Yes/No/Not available)?
    - Predictor selection methods for inclusion into the multivariable analysis:
        - All predictors were predetermined to be included in the analysis
        - Predictors were selected for inclusion based on univariate associations with the outcome
        - Others
    - Did any statistical transformation of candidate predictors occur (i.e. dichotomising a continuous or categorical variable) prior to inclusion in the multivariate modelling process (Yes/No/Not Available)?
        - If YES, what transformation procedure was applied?
    - Predictor selection methods during the multivariable modelling:
        - Full model approach (all predictors were predefined for the final model and no predictors were omitted).
        - Forward selection (candidate predictors were selected based on pre-specified criteria).
            - If forward selection was applied, which criteria/significance level were used?
                - P-value
                - Akaike's Information Criteria
                - R^2
                - Others

        - Backward elimination (all candidate predictors started in the model and were removed or kept based on a pre-specified criterion)
            - If backward elimination was applied, which criteria/ significance level were used?
                - P-value
                - Akaike's Information Criteria
                - R^2
                - Others
    - Were shrinkage techniques applied (Yes/No/Not available)?
        - If YES, which procedure was applied?
- Model performance:
    - Overall measures of model performance
        - R^2
        - Brier Score
    - Discrimination:
        - Area Under Curve/*c*-statistic
        - D-statistic
        - Others
    - Calibration:
        - Calibration plot
        - Calibration intercept and slope
        - Calibration table
        - Hosmer-Lemeshow test
        - Observed:Expected Ratio
        - Others.
    - Classification:
        - Sensitivity
        - Specificity
        - Positive Predictive Value
        - Negative Predictive Value
        - Net reclassification index
        - Others

        - Was the cut-point:
            - Predefined/made a priori?
            - Derived from the dataset?
- Model evaluation:
        - **External validation:** Were the model performance measures based on separate external data (Y/N/NA)?
            - If YES, how was the dataset different from the developmental dataset:
                - Temporal/differed in time
                - Different geographical location
                - Different setting
                - Different investigator
                - Others
        - **Internal validation:** Were the model performance measures based on the developmental dataset (Y/N/NA)?
            - Which approach was chosen to evaluate model performance?
                - Split-sample validation
                    - What was the percentage-wise allocation of participants?
                    - Was the split random to model development and validation(Y/N/NA)?
                - Cross-validation
                    - How many subsets were chosen?
                - Bootstrap validation
                - Jack-knife resampling
                - Others
                - None
- Model presentation:
    - What format did the study present their model in to permit calculations of individual risks?
        - Regression formula (comment)
        - Rounded scoring rules (comment)
        - Predefined risk groups (comment)

        - Were the risk-groups:
            - Predefined/made a priori?
            - Derived from the dataset?
    - Nomogram
    - Score chart
    - Others
    - None
- Sources of funding in the individual study.

Outcomes and prioritisation

Main outcomes:

The main outcome of this systematic review is to describe model performance. Secondary outcomes are to describe the following characteristics: Study setup, participants, final model predictors, outcomes together with model development, -evaluation and -presentation.

Risk of bias

The Prediction study Risk Of Bias Assessment Tool (PROBAST)[19] will be applied for risk of bias assessment. Two reviewers (GS and JRI both with no prior experience in risk of bias assessments) will independently assess for risk of bias. These will not be blinded to study titles or authors. If reporting is incomplete in order to make a complete assessment, we will try to contact authors of the concerned study. A maximum of two attempts will be done to contact the authors by e-mail. If e-mails are not responded within 1 month from the first e-mail sent, the data field will be labelled as "Unclear". Disagreement among the reviewers will be discussed. If agreement still is not reached, a third author (MGJ) will be consulted for arbitration. The total number of times arbitration by a third author was required will be given. Each domain rating will be reported instead of a summative score of all domains. Previously, one review on fall prediction models assessed reporting in included studies to be poor[12]. However, no standardised method of evaluating reporting in studies was reported. Thus, as a supplement to the risk of bias assessments, the newly published TRIPOD adherence tool[26] will be used to assess adherence to reporting guidelines for prediction modelling studies.

Data synthesis

Meta-analysis will not be considered due to this systematic review merely being descriptive. In the qualitative synthesis, information will be presented in text, figures, and tables of the included studies. Reporting of studies will be presented in tables by their publication year. Final model predictors will be presented in main categories in a figure.

Meta-bias

Presence of outcome reporting bias will be investigated by comparing the studies with their respective protocol if available. The following aspects will be considered:

- Was publication of the protocol done before recruitment of patients?
- Was the intended outcome in the protocol the same in the published study?

Confidence in cumulative estimate

Assessment of strength of evidence will be made using the PROBAST tool.

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Appendix 2: PRISMA checklist

See tables on the next page. Fields pertaining to meta-analyses have been labelled as not available (NA) since meta-analyses was not performed.

Section/topic	#	Checklist item	Reported on page #
TITLE			
Title	1	Identify the report as a systematic review, meta-analysis, or both.	#2
ABSTRACT			
Structured summary	2	Provide a structured summary including, as applicable: background; objectives; data sources; study eligibility criteria, participants, and interventions; study appraisal and synthesis methods; results; limitations; conclusions and implications of key findings; systematic review registration number.	#4
INTRODUCTION			
Rationale	3	Describe the rationale for the review in the context of what is already known.	#6
Objectives	4	Provide an explicit statement of questions being addressed with reference to participants, interventions, comparisons, outcomes, and study design (PICOS).	#6
METHODS			
Protocol and registration	5	Indicate if a review protocol exists, if and where it can be accessed (e.g., Web address), and, if available, provide registration information including registration number.	#6
Eligibility criteria	6	Specify study characteristics (e.g., PICOS, length of follow-up) and report characteristics (e.g., years considered, language, publication status) used as criteria for eligibility, giving rationale.	#6-8
Information sources	7	Describe all information sources (e.g., databases with dates of coverage, contact with study authors to identify additional studies) in the search and date last searched.	#8
Search	8	Present full electronic search strategy for at least one database, including any limits used, such that it could be repeated.	#8 + Appendix 3
Study selection	9	State the process for selecting studies (i.e., screening, eligibility, included in systematic review, and, if applicable, included in the meta-analysis).	#8-9 + Appendix 4
Data collection process	10	Describe method of data extraction from reports (e.g., piloted forms, independently, in duplicate) and any processes for obtaining and confirming data from investigators.	#9
Data items	11	List and define all variables for which data were sought (e.g., PICOS, funding sources) and any assumptions and simplifications made.	#9 + Appendix 5
Risk of bias in individual studies	12	Describe methods used for assessing risk of bias of individual studies (including specification of whether this was done at the study or outcome level), and how this information is to be used in any data synthesis.	#9-10
Summary measures	13	State the principal summary measures (e.g., risk ratio, difference in means).	#10

Synthesis of results	14	Describe the methods of handling data and combining results of studies, if done, including measures of consistency (e.g., I^2) for each meta-analysis.	**NA**

Section/topic	#	Checklist item	Reported on page #
Risk of bias across studies	15	Specify any assessment of risk of bias that may affect the cumulative evidence (e.g., publication bias, selective reporting within studies).	#10
Additional analyses	16	Describe methods of additional analyses (e.g., sensitivity or subgroup analyses, meta-regression), if done, indicating which were pre-specified.	**NA**
RESULTS			
Study selection	17	Give numbers of studies screened, assessed for eligibility, and included in the review, with reasons for exclusions at each stage, ideally with a flow diagram.	#10 + Fig 1 + Appendix 6-8
Study characteristics	18	For each study, present characteristics for which data were extracted (e.g., study size, PICOS, follow-up period) and provide the citations.	#10-12 + Fig 2 + Appendix 9-10
Risk of bias within studies	19	Present data on risk of bias of each study and, if available, any outcome level assessment (see item 12).	#12 + Table 1
Results of individual studies	20	For all outcomes considered (benefits or harms), present, for each study: (a) simple summary data for each intervention group (b) effect estimates and confidence intervals, ideally with a forest plot.	#12
Synthesis of results	21	Present results of each meta-analysis done, including confidence intervals and measures of consistency.	**NA**
Risk of bias across studies	22	Present results of any assessment of risk of bias across studies (see Item 15).	#12
Additional analysis	23	Give results of additional analyses, if done (e.g., sensitivity or subgroup analyses, meta-regression [see Item 16]).	**NA**
DISCUSSION			
Summary of evidence	24	Summarize the main findings including the strength of evidence for each main outcome; consider their relevance to key groups (e.g., healthcare providers, users, and policy makers).	#12-13
Limitations	25	Discuss limitations at study and outcome level (e.g., risk of bias), and at review-level (e.g., incomplete retrieval of identified research, reporting bias).	#13
Conclusions	26	Provide a general interpretation of the results in the context of other evidence, and implications for future research.	#13-15
FUNDING			

Funding	27	Describe sources of funding for the systematic review and other support (e.g., supply of data); role of funders for the systematic review.	#10

Appendix 3: search strategy

Pubmed.gov

((((((home-dwell*[tw] OR "Independent Living"[Mesh] OR Independent*[tw] OR community-dwell*[tw] OR home-based*[tw] OR community-living*[tw]))

AND ("Aged"[Mesh] OR aged[tw] OR senior*[tw] OR elder*[tw] OR old[tw] OR older[tw])))) AND ("Accidental Falls"[Mesh] OR fall*[Text Word])))

AND ((((Validat*[tw] OR Predict*[ti] OR Rule*[tw]) OR (Predict*[tw] AND (Outcome*[tw] OR Risk*[tw] OR Model*[tw])) OR ((History[tw] OR Variable*[tw] OR Criteria [tw]OR Scor*[tw] OR Characteristic*[tw] OR Finding*[tw] OR Factor*[tw]) AND (Predict*[tw] OR Model*[tw] OR Decision*[tw] OR Identif*[tw] OR Prognos*[tw])) OR (Decision*[tw] AND (Model*[tw] OR Clinical*[tw] OR "Logistic Models"[MESH])) OR (Prognostic[tw] AND (History[tw] OR Variable*[tw] OR Criteria[tw] OR Scor*[tw] OR Characteristic*[tw] OR Finding*[tw] OR Factor*[tw] OR Model*[tw]))))) OR ((((((((((("ROC Curve"[Mesh]) OR stratificat*[tw]) OR discriminat*[tw]) OR c statistic*[tw]) OR Area under the curve*[tw]) OR AUC[tw]) OR Calibrat*[tw]) OR Indices[tw]) OR Algorithm*[tw]) OR Multivariable*[tw])) OR ((Predict*[tw] OR Predictive value of tests[mh] OR Scor*[tw] OR Observ*[tw] OR Observer variation[mh])))))

Embase:

('falling'/exp OR fall*:ti,ab,kw)

AND ('aged'/exp OR aged:ti,ab,kw OR senior*:ti,ab,kw OR elder*:ti,ab,kw OR old:ti,ab,kw OR older:ti,ab,kw)

AND (validat* OR rule* OR (predict* AND (outcome* OR risk* OR model*)) OR ((history OR variable* OR criteria OR scor* OR characteristic* OR finding* OR factor*)

AND (predict* OR model* OR decision* OR identif* OR prognos*)) OR (decision* AND (model* OR clinical* OR 'statistical model'/exp)) OR (prognostic AND (history OR variable* OR criteria OR scor* OR characteristic* OR finding* OR factor* OR model*)) OR 'receiver operating characteristic'/exp OR stratificat* OR discriminat* OR 'c statistic*' OR 'area under the curve*' OR auc OR calibrat* OR indices OR algorithm* OR multivariable* OR predict* OR 'predictive value'/exp OR scor* OR observ* OR 'observer variation'/exp) AND ('community living'/exp OR 'at home':ti,ab,kw OR (((community OR home OR independent*) NEAR/3 (dwell* OR based OR live OR living)):ti,ab,kw) OR 'home accident'/exp OR 'community dwelling person'/exp)

CINAHL:

((MH "Community Living") OR (MH "Assisted Living") OR ((community OR home OR independent*) N3 (dwell* OR based OR live OR living)) OR (MH "Accidents, Home") OR at home) AND ((MH "Accidental Falls") OR fall*)

AND ((MH "Aged") OR (MH "Aged, 80 and Over") OR (MH "Frail Elderly") OR aged OR senior* OR elder* OR old OR older)

AND (validat* OR rule* OR (predict* AND (outcome* OR risk* OR model*)) OR ((history OR variable* OR criteria OR scor* OR characteristic* OR finding* OR factor*) AND (predict* OR model* OR decision* OR identif* OR prognos*)) OR (decision* AND (model* OR clinical* OR (MH "Models, Statistical"))) OR (prognostic AND (history OR variable* OR criteria OR scor* OR characteristic* OR finding* OR factor* OR model*)) OR (MH "ROC Curve") OR stratificat* OR discriminat* OR 'c statistic*' OR 'area under the curve*' OR auc OR calibrat* OR indices OR algorithm* OR multivariable* OR predict* OR (MH "Predictive Value of Tests") OR scor* OR observ*)

Psycinfo
http://psycnet.apa.org.auh.aub.aau.dk/permalink/19512998-9a97-e90a-722c-bd157326fa55

((Any Field: (validat*) OR Any Field: (rule*) OR (Any Field: (predict*) AND (Any Field: (outcome*) OR Any Field: (risk*) OR Any Field: (model*))) OR ((Any Field: (history) OR Any Field: (variable*) OR Any Field: (criteria) OR Any Field: (scor*) OR Any Field: (characteristic*) OR Any Field: (finding*) OR Any Field: (factor*)) AND (Any Field: (predict*) OR Any Field: (model*) OR Any Field: (decision*) OR Any Field: (identif*) OR Any Field: (prognos*))) OR (Any Field: (decision*) AND (Any Field: (model*) OR Any Field: (clinical*))) OR (Any Field: (prognostic) AND (Any Field: (history) OR Any Field: (variable*) OR Any Field: (criteria) OR Any Field: (scor*) OR Any Field: (characteristic*) OR Any Field: (finding*) OR Any Field: (factor*) OR Any Field: (model*))) OR Any Field: (stratificat*) OR Any Field: (discriminat*) OR Any Field: ('c statistic*') OR Any Field: ('area under the curve*') OR Any Field: (ROC) OR Any Field: (auc) OR Any Field: (calibrat*) OR Any Field: (indices) OR Any Field: (algorithm*) OR Any Field: (multivariable*) OR Any Field: (predict*) OR Any Field: (scor*) OR Any Field: (observ*))))

AND ((((((Any Field: ('at home'))) OR ((((Any Field: (community))) OR ((Any Field: (home))) OR ((Any Field: (independent*)))) NEAR/3 (((Any Field: (dwell*))) OR ((Any Field: (based))) OR ((Any Field: (live))) OR ((Any Field: (living))))))) OR ((((IndexTermsFilt: ("Home Accidents"))))))

AND (((Any Field: (aged))) OR ((Any Field: (elder*))) OR ((Any Field: (old))) OR ((Any Field: (older))) OR ((Any Field: (senior*))))

AND (((IndexTermsFilt: ("Falls"))) OR ((Any Field: (fall*)))))

Cochrane Library:
ID Search

#1 MeSH descriptor: [Accidental Falls] explode all trees
#2 fall*:ti,ab,kw
#3 #1 OR #2
#4 MeSH descriptor: [Aged] explode all trees
#5 aged:ti,ab,kw
#6 senior*:ti,ab,kw
#7 elder*:ti,ab,kw
#8 old:ti,ab,kw
#9 older:ti,ab,kw
#10 #4 OR #5 OR #6 OR #7 OR #8 OR #9
#11 MeSH descriptor: [Independent Living] this term only
#12 "at home":ti,ab,kw
#13 MeSH descriptor: [Accidents, Home] explode all trees
#14 #3 or #13
#15 (((community OR home OR independent*) NEAR/3 (dwell* OR based OR live OR living)):ti,ab,kw)
#16 #11 OR #12 OR #13 OR #15
#17 #14 AND #16 AND #10
#18 MeSH descriptor: [Logistic Models] explode all trees
#19 MeSH descriptor: [ROC Curve] explode all trees
#20 MeSH descriptor: [Predictive Value of Tests] explode all trees
#21 MeSH descriptor: [Observer Variation] explode all trees
#22 ((((Validat* OR Predict*:ti OR Rule*) OR (Predict* AND (Outcome* OR Risk* OR Model*)) OR ((History OR Variable* OR Criteria OR Scor* OR Characteristic* OR Finding* OR Factor*) AND (Predict* OR Model* OR Decision* OR Identif* OR Prognos*)) OR (Decision* AND (Model* OR Clinical* OR #18)) OR (Prognostic AND (History OR Variable* OR Criteria OR Scor* OR Characteristic* OR Finding* OR Factor* OR Model*)))) OR ((((((((((#19) OR stratificat*) OR discriminat*) OR c statistic*) OR Area under the curve*) OR AUC) OR Calibrat*) OR Indices) OR Algorithm*) OR Multivariable*)) OR ((Predict* OR #20 OR Scor* OR Observ* OR #21))))
#23 #17 AND #22

Web of Science:
#1 ts=fall*
#2 ts=(aged OR senior* OR elder* OR old OR older)
#3 ts=((validat* OR rule* OR (predict* AND (outcome* OR risk* OR model*)) OR ((history OR variable* OR criteria OR scor* OR characteristic* OR finding* OR factor*) AND (predict* OR model* OR decision* OR identif* OR prognos*)) OR (decision* AND (model* OR clinical* OR "statistical model")) OR (prognostic AND (history OR variable* OR criteria OR scor* OR characteristic* OR finding* OR

factor* OR model*)) OR ("receiver operating characteristic" OR stratificat* OR discriminat* OR "c statistic" OR "area under the curve*" OR auc OR calibrat* OR indices OR algorithm* OR multivariable* OR predict* OR "predictive value" OR scor* OR observ* OR "observer variation")))
#4 ts=("community living" OR "at home" OR ((community OR home OR independent*) NEAR/3 (dwell* OR based OR live OR living)) OR "home accident" OR "community dwelling person")
#4 AND #3 AND #2 AND #1

PROSPERO:
https://www.crd.york.ac.uk/prospero

Clinicaltrials.gov:
https://clinicaltrials.gov/ct2/results?cond=falling+and+elderly+or+older+adults&term=&cntry=&state=&city=&dist=

WHO International Clinical Trials Registry Platform:
http://apps.who.int/trialsearch/

Open Grey:
http://www.opengrey.eu/search/request?q=Falling+AND+Elderly+OR+Older+adults

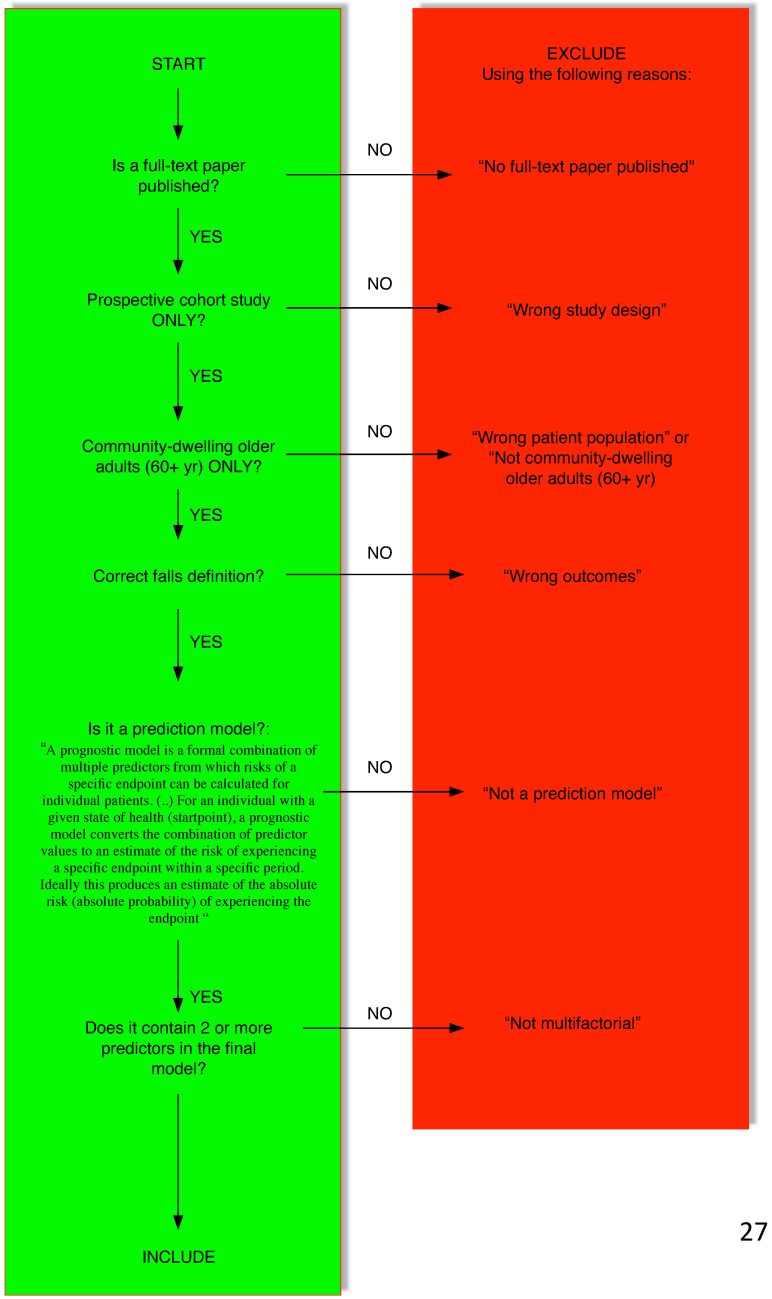
GIN:
https://www.g-i-n.net/library/international-guidelines-library/international-guidelines-library/@@guideline_search_results?basic-searchable-text=falling+and+elderly+or+older+adults&type=basic&action=Search&advanced-authors=&diseases=&meshterm=&search=

NICE:
https://www.nice.org.uk/Search?q=Falling+AND+Elderly+OR+Older+adults

CRD/HTA:
https://www.crd.york.ac.uk/CRDWeb/

SIGN:
https://www.sign.ac.uk/our-guidelines.html

Appendix 4: prioritised list for exclusion reasons



Appendix 5: data extraction items

- General study information:
  - Authors
  - Year of publication
  - Study design
  - Type of prediction modelling study:
    - Developmental without external validation
    - Developmental with external validation
    - External model validation without model updating
    - External model validation with model updating
    - Others
  - Country of origin
  - Setting where candidate predictors were measured
  - Number of study centres
  - Inclusion criteria
  - Exclusion criteria
  - Sample size
  - Methods for participant recruitment/sampling:
    - Consecutive sampling
    - Convenience sampling
    - Probability sampling
    - Others

    - Dates of participant recruitment
    - Duration of follow-up
    - How many participants completed follow-up percentage-wise?
- Participants:
    - Gender
    - Age
    - Fall history
- Outcome:
    - Outcome definition
        - Was it pre-specified?
    - Type of fall recording/method of outcome measurement
    - Was the same outcome definition and recording method used in all participants (Yes/No/Not Available)?
    - Was the outcome assessor blinded towards predictors (Yes/No/Not Available)?
    - Number of falls
    - Number of fallers
    - Number of non-fallers
    - Number of frequent fallers
    - Fall-rate per person per year
    - Summary of follow-up period
- Candidate predictors:
    - Number of candidate predictors studied
    - Definitions of candidate predictors
    - Methods for measuring candidate predictors

  - Number of outcomes (falls) in relation to number of candidate predictors (events per variable (EPV))
- Missing data:
  - Number of participants with missing data (both predictors and outcomes) in total
  - Did participants with missing data differ from those without missing data (Yes/No/Not Available)?
  - Number of participants with missing data in total for each predictor
  - Method of handling missing data
    - Single imputation
    - Multiple imputation
    - Participants with missing data were excluded from the analysis (complete case analysis)
    - Others (comment)
  - Were participants with missing data included in the model development, validation or updating (Yes/No/Not Available)?
- Model development (not relevant if the prediction modelling study does not include model development):
  - Type of model:
    - Linear regression
    - Logistic regression
    - Survival analysis
    - Others (comment)
  - Were assumptions for the model checked (Yes/No/Not available)?
  - Were assumptions for the model satisfied (Yes/No/Not available)?
  - Predictor selection methods for inclusion into the multivariable analysis:
    - All predictors were predetermined to be included in the analysis
    - Predictors were selected for inclusion based on univariate associations with the outcome
    - Others

- Did any statistical transformation of candidate predictors occur (i.e. dichotomising a continuous or categorical variable) prior to inclusion in the multivariate modelling process (Yes/No/Not Available)?
  - If YES, what transformation procedure was applied?
- Predictor selection methods during the multivariable modelling:
  - Full model approach (all predictors were predefined for the final model and no predictors were omitted)
  - Forward selection (candidate predictors were selected based on pre-specified criteria)
    - If forward selection was applied, which criteria/significance level were used?
      - P-value
      - Akaike's Information Criteria
      - R^2
      - Others
  - Backward elimination (all candidate predictors started in the model and were removed or kept based on a pre-specified criterion)
    - If backward elimination was applied, which criteria/ significance level were used?
      - P-value
      - Akaike's Information Criteria
      - R^2
      - Others
- Were shrinkage techniques applied (Yes/No/Not available)?
  - If YES, which procedure was applied?

- Model performance:
  - Overall measures of model performance
    - R^2

        - Brier Score
    - Discrimination:
        - Area Under Curve/*c*-statistic
        - D-statistic
        - Others
    - Calibration:
        - Calibration plot
        - Calibration intercept and slope
        - Calibration table
        - Hosmer-Lemeshow test
        - Observed:Expected Ratio
        - Others
    - Classification:
        - Sensitivity
        - Specificity
        - Positive Predictive Value
        - Negative Predictive Value
        - Net reclassification index
        - Others
        - Was the cut-point:
            - Predefined/made a priori?
            - Derived from the dataset?
- Model evaluation:

- **External validation:** Were the model performance measures based on separate external data (Y/N/NA)?
  - If YES, how was the dataset different from the developmental dataset:
    - Temporal/differed in time
    - Different geographical location
    - Different setting
    - Different investigator
    - Others
- **Internal validation:** Were the model performance measures based on the developmental dataset (Y/N/NA)?
  - Which approach was chosen to evaluate model performance?
    - Split-sample validation
      - What was the percentage-wise allocation of participants?
      - Was the split random to model development and validation(Y/N/NA)?
    - Cross-validation
      - How many subsets were chosen?
    - Bootstrap validation
    - Jack-knife resampling
    - Others
    - None

- Model presentation:
  - What format did the study present their model in to permit calculations of individual risks?
    - Regression formula (comment)
    - Rounded scoring rules (comment)
    - Predefined risk groups (comment)

- Were the risk-groups:
  - Predefined/made a priori?
  - Derived from the dataset?
- Nomogram
- Score chart
- Others
- None

- Sources of funding in the individual study

We used the following definitions of developmental studies and validation studies:

- Developmental study: "Model development studies aim to derive a prediction model by selecting predictors and combining them into a multivariable model"[1].
- Validation study: A fully specified existing prognostic model including both predictors and their coefficients [2].
  - Studies with prespecified predictors, but without any coefficients were classified as developmental studies.

1 Collins GS, Reitsma JB, Altman DG, *et al.* Transparent reporting of a multivariable prediction model for individual prognosis or diagnosis (TRIPOD): the TRIPOD Statement. *BMC Med* 2015;**13**:1. doi:10.1186/s12916-014-0241-z

2 Altman DG, Vergouwe Y, Royston P, *et al.* Prognosis and prognostic research: Validating a prognostic model. *BMJ* 2009;**338**:1432–5. doi:10.1136/bmj.b605

Appendix 6: studies excluded during screening of titles and abstracts:

See separate PDF file: "Appendix 6".

Appendix 7: possibly relevant studies in other languages excluded during screening of titles and abstract:

Title	Author	Year	Language:	Reference:
Fall Prediction Model for Community-dwelling Elders based on Gender	Eun Suk, Yun	2012	Korean	J Korean Acad Nurs. 2012;42(6):810-818. doi:10.4040/jkan.2012.42.6.810
Fall risk and fracture. Aging and fall/fracture	Kozaki, K.	2013	Japanese	Clin Calcium. 2013;23(5):653-660
Fall risk assessment in regular exercising elderly women	Kikuchi, R.; Kozaki, K.; Kawashima, Y.; Iwata, A.; Hasegawa, H.; Igata, A.; Toba, K.	2008	Japanese	Nihon Ronen Igakkai Zasshi. 2008;45(5):526-531. doi:10.3143/geriatrics.45.526
Risk profiles and preventive measures of falls in elderly persons	Tromp, E	2002	Dutch	Tijdschr Gerontol Geriatr. 2002;33(1):21-25.
Fall-related factors in a cohort of elderly community residents	Rodriguez Perracini, M.; Ramos, L. R.	2002	Spanish	Rev Saude Publica. 2002;36(6):709-716. doi:10.1590/s0034-89102002000700008
Identifying the elderly at risk for falling and accompanying protocols	Galinsky, D.; Fried, V.; Biderman, A.; Cwikel, J.; Ben Moshe, Y.	2000	Hebrew	Harefuah. 2000;138(3):189-271.
Impact of fall risk and fear of falling on mobility of independently living senior citizens transitioning to frailty: Screening results concerning fallprevention in the community	Anders, J.; Dapp, U.; Laub, S.; Von Renteln-Kruse, W.	2007	German	Z Gerontol Geriatr. 2007;40(4):255-267. doi:10.1007/s00391-007-0473-z

Appendix 8: studies excluded during full-text screening.

See separate PDF file: "Appendix 8".

Appendix 9: supplementary table 1 with characteristics of included studies

Supplementary Table 1 Characteristics of included studies

First author, year, country, study type	Study characteristics (sample size, age distribution, % female, % of sample with prior falls)	Outcomes (n; %) and length of follow-up	Statistical model and validation technique	Final models and their presentation (model no. (outcome): predictors with/without weights)	Model performance
Maki et al. [1], 1994, Canada Development study study	n = 100 Age, mean (SD): 83 (6) years Female: 83% Prior falls: 46.8%	Any falls (59; 59%) Recurrent falls (23; 23%) Follow-up: 12 months	Logistic regression Cross-validation (n-1)	**Model** 1 (any falls): Spontaneous mediolateral sway (root-mean-square) with eyes blindfolded; induced sway in anterior-posterior direction with eyes open (mean COP location / length of base-of-support) **Model** 2 (recurrent falls): Induced sway in mediolateral direction with eyes blindfolded (mean coherence of the input-output model); induced sway in mediolateral direction with eyes blindfolded (Relative COP overshoot in the predicted transient response)	**Model** 1: AUC (SE): 0.76 (0.05) Calibration: no information SN: 78% (43/55) SP: 50% (18/36) **Model** 2: AUC (SE): 0.87 (0.05) Calibration: no information SN: 53% (9/17) SP: 89% (31/35)
Brauer et al. [2], 2000, Australia Developmental study	n = 100 Age, mean (SD): 71 (5) years Female: 100% Prior falls: 35%	Any falls (35; 35%) Follow-up: 6 months	Logistic regression Cross-validation (no information on subsets)	**Model** 1 (any falls): Gluteus medius onset time; Movement time in a high preparation step task; Step time in a high preparation step task; Maximum COP excursion when moving to the right LOS; COP maximum mediolateral velocity; Total distance moved in quiet stance **Model** 2 (any falls): Movement time in a high preparation step task; step time in a high preparation step task; total time in a high preparation step task; movement time in a neutral preparation step task; step time in a neutral preparation step task; total time in a neutral preparation step task **Model** 3 (any falls): Gluteus medius in a neutral preparation step task; tensor fascia latae in a neutral preparation step task; hip adductors in a neutral preparation step task; gastrocnemius onset times in a neutral preparation step task; gluteus medius in a high preparation step task; tensor fascia latae in a high preparation step task; hip adductors in a high	**Model** 1: AUC: no information Calibration: no information SN: 51% SP: 91% Total predictive ability: 77% **Model** 2: AUC: no information Calibration: no information SN: 34% SP: 89% Total predictive ability: 70% **Model** 3: AUC: no information Calibration: no information SN: 23% SP: 88% Total predictive ability: 65%

				preparation step task; gastrocnemius onset times in a high preparation step task **Model** 4 (any falls): COP maximum mediolateral velocity with eyes open; COP maximum mediolateral velocity with eyes closed; COP position in quiet stance with eyes open; COP position in quiet stance with eyes closed; COP total distance moved in quiet stance with eyes open; COP total distance moved in quiet stance with eyes closed **Model** 5 (any falls): COP maximum excursion when moving to the right LOS; COP maximum excursion when moving to the left LOS; COP maximum excursion when moving to the anterior LOS; COP maximum excursion when moving to the posterior LOS **Model** 6 (any falls): Left Functional Reach; Right Functional Reach; Right Lateral Reach; Left Lateral Reach; Step-Up number; Berg Balance Scale score **Model** 7 (any falls): Left Functional Reach; Right Functional Reach; Right Lateral Reach; Left Lateral Reach; Step-Up number; Berg Balance Scale score; Gluteus medius onset time; Movement time in a high preparation step task; Step time in a high preparation step task; Maximum COP excursion when moving to the right LOS; COP maximum mediolateral velocity; Total distance moved in quiet stance	**Model** 4: AUC: no information Calibration: no information SN: 29% SP: 88% Total predictive ability: 67% **Model** 5: AUC: no information Calibration: no information SN: 6% SP: 97% Total predictive ability: 65% **Model** 6: AUC: no information Calibration: no information SN: 12% SP: 95% Total predictive ability: 66% **Model** 7: AUC: no information Calibration: no information SN: 59% SP: 86% Total predictive ability: 77%
Tromp et al. [3], 2001, The Netherlands, Development study	n = 1,374 Age, mean (SD): 75.2 (6.5) years Age, range: 64.8-88.6 years Of the 1,285 with complete follow-up, female: 51%	Any falls (428; 31.1%) Recurrent falls (147; 10.7%) Follow-up: 12 months	Logistic regression No information on model validation	**Model** 1 (any falls): Regression table with regression coefficients: constant: no information; previous falls: 0.90; urinary incontinence: 0.46; visual impairment: 0.44; use of benzodiazepines: 0.44 Score chart - previous falls: 5; urinary incontinence: 2; visual impairment: 2; use of benzodiazepines: 2	**Model** 1: AUC: 0.65 Calibration: no information

	Prior falls: 31%			**Model** 2 (recurrent falls): Regression table with regression coefficients: constant: no information; previous falls: 0.99; urinary incontinence: 0.53; visual impairment: 0.82; use of benzodiazepines: 0.54 Score chart: previous falls: 5; urinary incontinence: 3; visual impairment: 4; use of benzodiazepines: 3	**Model** 2: AUC: 0.71 Calibration: no information Cut-off: 7 points SN: 54% SP: 79% PPV (CI): 24.9% (22.5-27.3%) NPV (CI): 93% (91.6-94.4%)
Stalenhoef et al. [4], 2002, The Netherlands, Development study	n = 302 Of the 287 with complete follow-up, age, mean (SD): - Female: 78.5 (5.2) years - Male: 77.2 (4.9) years Of the 287 with complete follow-up, female: 60% Prior falls: 66%	Recurrent falls (46; 15.2%) Follow-up: 9 months	Logistic regression No information on model validation	**Model** 1 (recurrent falls): Regression table including regression coefficients with SE: constant: -2.28; female gender: -0.39 (0.4); age >= 80 years: 0.04 (0.39); falls >= 2 in previous year: 1.14 (0.39); depression - SCL90 >= 22: 0.78 (0.37); hand dynamometry (men <= 22 kg or women: <= 12 kg: 1.14 (0.38); postural sway abnormal: 1.36 (0.58) Rounded scoring rule - men: age >= 80 years: was not included due to low impact; falls >= 2 in previous year: 6; depression - SCL90 >= 22 4; hand dynamometry (Men <= 22 kg or Women: <= 12 kg): 6; postural sway abnormal: 7 Rounded scoring rule – women: age >= 80 years: Was not included due to low impact; falls >= 2 in previous year: 4; depression - SCL90 >= 22: 2; hand dynamometry (men <= 22 kg or women: <= 12 kg): 4; postural sway abnormal: 5	**Model** 1: AUC: 0.79 Calibration: "The comparison of the percentages predicted probability with the percentage of observed recurrent fallers showed a general agreement. The predicted values of the model, calculated according to the Hosmer Lemeshow goodness of fit, showed good fit." Cut-off: 0.30 SN: 59% SP: 87% PPV: 52% NPV: 90%
Stel et al. [5], 2003, The Netherlands, Development study	n = 1,365 Age, mean (SD): 75.3 (6.4) years Age, range: 64.8-88.6 years Female: 51% Prior falls: 31%	Recurrent falls (337; 24.7%) Follow-up: - Primary length of follow-up: 3 years - Secondary length of follow-up: 1 year.	Tree-structured survival analysis No information on model validation	**Model** 1 (recurrent falls): Classification tree with a follow-up of 3 years: fall history, function limitations, dizziness, performance test score, grip strength, alcohol consumption, pain, educational level, and physical activity **Model** 2 (recurrent falls): Classification tree with a follow-up of 1 year: fall history, function limitations, and grip strength	**Model** 1: AUC: no information Calibration: no information **Model** 2: AUC: no information Calibration: no information
Boulgarides et al. [6], 2003, USA,	n = 106 Age, mean (SD):	Recurrent falls (20; 18.9%)	Logistic regression	**Model** 1 (recurrent falls): Regression table with coefficients and SE:	**Model** 1: AUC: no information Calibration: no information

Development study	74.02 (5.64) years Age range: 65-90 years Of 99 participants included in analysis: female: 61% Prior falls: 50.5%	Follow-up: 12 months	No information on model validation	constant: no information; postural sway while standing on a firm surface with eyes closed: 1.786 (1.332); age: 0.072 (0.048); sex: 0.822 (0.540)	% Correct prediction: 80.8%, though only predicted 2/20 of multiple fallers SN: 10% SP: 98.7%
Nandy et al. [7], 2004, UK, Development study	n = 510 Of the 345 with complete follow-up, age, mean (SD): 74.4 (6.4) years Of the 345 with complete follow-up, female: 55% Prior falls: 25%	Any falls (no information) Follow-up: 6 months	Only SN, SP, PPV, NPV, and Youden's index were calculated No information on model validation	**Model** 1 (any falls): Three or more of the following risk factors: history of falling in the previous year, taking four or more prescribed medications, history of stroke or Parkinson's disease, and reported problems with balance and loss of proximal muscle strength	**Model** 1: AUC: no information Calibration: no information SN: 0.42 (0.32-0.54) SP: 0.92 (0.88-0.94) PPV: 0.57 (0.43-0.69) NPV: 0.86 (0.83-0.89) Youden's Index: 0.339 (0.185-0.493)
Pluijm et al. [8], 2006, The Netherlands, Development study	n = 1,365 Age, mean (SD): 75.3 (6.4) years Age, range: 64.8-88.6 years Female: 51.1% Prior falls: 14.2%	Recurrent falls (457; 33.5%) Follow-up: - Primary: 3 years - Secondary: 1 year	Logistic regression No information on model validation	**Model** 1 (recurrent falls within 3 years): Regression table with regression coefficients: constant: - 2.19; two or more previous falls: 0.71; dizziness: 0.77; functional limitations: 0.53; weak grip strength: 0.55; low body weight: 0.37; fear of falling: 0.34; the presence of dogs/cats in the household: 0.40; a high education level: 0.21; drinking of 18 or more alcoholic consumptions per week: 0.11; interaction term (high education × 18 or more alcohol consumptions per week): 0.86; interaction term (two or more previous falls × fear of falling): 0.83 Score chart: two or more previous falls: 4; dizziness: 4; functional limitations: 3; weak grip strength: 3; low body weight: 2; fear of falling: 2; the presence of dogs/cats in the household: 2; a high education level: 1; drinking 18 or more alcoholic consumptions per week: 1; interaction term (high education × 18 or more alcohol consumptions per week): 4; interaction term (two or more previous falls × fear of falling): 4 **Model** 2 (recurrent falling within 1 year): Regression table with regression coefficients: constant: - 3.13; two or more previous falls: 0.64; dizziness: 0.52; functional limitations: 0.39; weak grip strength: 0.65; low body weight: 0.32;	**Model** 1: AUC (CI): 0.71 (0.67-0.74) Calibration: The Hosmer-Lemeshow goodness-of-fit test for the multiple logistic regression was not significant (p=0.56), indicating that the model fits the data well Cut-off: 5 points SN: 59% SP: 71.4% PPV: 38.6% NPV: 85.1% **Model** 2: AUC: (CI): 0.72 (0.67- 0.77) Calibration: The Hosmer-Lemeshow goodness-of-fit test for the multiple logistic regression

				fear of falling: 0.09; the presence of dogs/cats in the household: 0.81; a high educational level: 0.08; drinking of 18 or more alcoholic consumptions per week: - 0.15; interaction term (high education × 18 or more alcohol consumptions per week): 0.87; interaction term (two or more previous falls × fear of falling): 1.15	was not significant (p=0.94), indicating that the model fits the data well
Okochi et al. [9], 2006, Japan, Development study	n = 1,734 Age, mean (SD): 75.8 (6.8) years Female: no information Prior falls: 16%	Any falls (208; 12.0%) Follow-up: 6 months	Logistic regression Split-sample validation (random split, 50%/50%)	**Model** 1 (any falls): Scoring system from 0-13 based on the odds ratio at an integer level from logistic regression: history of falls - probable score 0/5; do you feel your walking speed has declined recently - probable score 0/2; do you use cane when you walk - probable score 0/2; is your back bended: probable score 0/2; do you take more than five kinds of prescription medicines - probable score 0/2	**Model** 1: AUC (95% CI): 0.74 (0.69-0.79) Calibration: no information Cut-off: 6 SN: 68% SP: 70% PPV: 27.9% Negative predictive power: 93%
Lindemann et al. [10], 2008, Germany, Development study	n = 65 Age, mean (SD): 67.7 (6.0) years Female: 57% Prior falls: 45%	Any falls (30; 46.2%) Follow-up: 12 months	The cut-off values for differentiating between persons, who fell and persons who did not, were defined for each parameter as the point on the Receiver Operating Characteristic curve with the minimal Euclidian distance to the point (0/1) No information on model validation	**Model** 1 (any falls): Adjusted mean valid step length (cut-off: 64% of body height), and at least one fall in previous year **Model** 2: (any falls): Adjusted max. valid step length (cut-off: 66% of body height), and at least one fall in previous year	**Model** 1: AUC and calibration: author response: "The information in the paper is the only we can provide. New calculations are not possible" SN (CI): 93% (86.7-100) SP (CI): 54% (40.5-67.1) PPV (CI): 70% (57.8-82.2) NPV (CI): 88% (78.7-96.3) +LR: 2.0 -LR: 0.1 **Model** 2: AUC: no information Calibration: no information SN (CI): 90% (82-98) SP (CI): 58% (44.5-70.9) PPV (CI): 71% (58.9-83.2) NPV (CI): 83% (73.4-93.3) +LR: 2.1 -LR: 0.2
Lamb et al. [11], 2008, USA, Development study	n = 1,002 Age, mean (SD): 78 (8.1) years	Any falls (346; 34.5%) Follow-up: 12 months	Tree-based classification Cross-validation (20 subsets)	**Model** 1 (any falls): Decision tree with self-report algorithm: how many falls have you had in the last year?; how often do you have problems balancing while	**Model** 1: AUC: no information Calibration: no information Fall probability threshold:

	Of the 885 included, female: 100% Of 830 included, prior falls: 34%			walking?; how much difficulty do you have with activities of daily living? **Model** 2 (any falls): Decision tree with self-report and performance item algorithm: how many falls have you had in the last year?; how often do you have problems balancing while walking?; knee extensor strength test; 4-metre usual gait speed; Body Mass Index	>= 0.34; SN: 0.59; SP: 0.64; +LR: 1.64; -LR: 0.64; Diagnostic Odds Ratio: 2.56 Fall probability threshold: >= 0.44; SN: 0.46; SP: 0.77; +LR: 2.00; -LR: 0.70; Diagnostic Odds Ratio: 2.85 Fall probability threshold: >= 0.55; SN: 0.32; SP: 0.87; +LR: 2.46; -LR: 0.78; Diagnostic Odds Ratio: 3.15 Fall probability threshold: >= 0.62; SN: 0.09; SP: 0.96; +LR: 2.25; -LR: 0.95; Diagnostic Odds Ratio: 2.37 **Model** 2: AUC: no information Calibration: no information Fall probability threshold: >= 0.25; SN: 0.78; SP: 0.46; +LR: 1.44; -LR: 0.48; Diagnostic Odds Ratio: 3.02 Fall probability threshold: >= 0.33; SN: 0.73; SP: 0.56; +LR: 1.66; -LR: 0.48; Diagnostic Odds Ratio: 3.44 Fall probability threshold: >= 0.42; SN: 0.54; SP: 0.74 +LR: 2.08; -LR: 0.62; Diagnostic Odds Ratio: 3.34 Fall probability threshold: >= 0.46; SN: 0.47; SP: 0.80; +LR: 2.35; -LR: 0.66; Diagnostic Odds Ratio: 3.54 Fall probability threshold: >= 0.56; SN: 0.33; SP: 0.90

					+LR: 3.30; -LR: 0.74; Diagnostic Odds Ratio: 4.43 Fall probability threshold: >= 0.69; SN: 0.16; SP: 0.97 +LR: 5.33; -LR: 0.87; Diagnostic Odds Ratio: 6.15
Delbaere et al. [12], 2010, Australia, Development study	n = 500 Age, mean (SD): 77.9 (4.1) years Female: 54% Prior falls: 29.6%	Recurrent falls (94; 18.8%) Follow-up: 12 months	Classification and Regression Tree (CRT) No information on model validation	**Model** 1 (recurrent falls): Risk groups: - Low risk: Physiological fall risk (Physiological Profile Assessment) <0.60. Subgroups were made from the Disability score >0. If Disability score >0, further subdivision was made using Incidental and Planned Exercise Questionnaire < 4hrs/week - High risk group: Physiological fall risk (Physiological Profile Assessment) >=0.60. Subgroups were made from Trail-Making-Test time <50. If Trail-Making-Test > 50, further subdivision was made using poor coordinated stability (error score >= 15). If score >= 15, further subdivision was done using Incidental and Planned Exercise Questionnaire > 0	**Model** 1: AUC and calibration: "We didn't calculate an AUC or related measure for our tree and our sample was not big enough to run a calibration analysis as well. No other classification measures were calculated " (author response)
Yamashita et al. [13], 2011, USA, Development study	n = 23,417 Age, mean (SD): 76.1 (8.94) years Female: 79% Prior falls: 3%	Any falls (approx. 1,400 (5.9%) Follow-up: between one day and 18 months due to the study using an open cohort design	Logistic regression No information on model validation	**Model** 1 (any falls): Regression table with coefficients: constant: no information; fall history: 0.997; female: 0.133; age: 0.013; blacks: -0.334; others: -0.363; married: -0.137; Alzheimer's disease: 0.055; cancer: -0.307; cataracts: -0.21; dementia: -0.135; depression: 0.334; diabetes: -0.034; emphysema: -0.171; glaucoma: 0.118; incontinence: 0.189; Parkinson's disease: 0.261; stroke: 0.103; vertigo: 0.085; total number of medications: 0.029; activities of daily living score: -0.07; instrumental activities of daily living score: 0.01; gait-shuffling: 0.027; gait-unsteady: 0.178; grasp-tremors: 0.426; grasp-weakness: -0.451; joint pain: 0.129; recent weight loss: 0.332; medication administration: 0.119; need for supervision: -0.265	**Model** 1: AUC: 0.61 Calibration: no information
Panzer et al. [14], 2011, USA, Development study	n = 74 Non-fallers: - Age, range: 65-87 years - Age, mean (SD): 75.1 (6.5) years	Recurrent falls (40; 54.1%) Follow-up: 12 months	Only sensitivity and specificity were calculated	**Model** 1 (recurrent falls): Multiple falls, gait velocity, turn time, turn number of steps, down 3 stairs, and step in tub **Model** 2 (recurrent falls):	**Model** 1: AUC: no information Calibration: no information Extracted from figure 2: SN: 52%; SP: 55%

	Fallers: - Age, range: 70-94 years - Age, mean (SD): 80.1 (6.2) years Female: no information Prior falls: 63.5%		No information on model validation	Multiple falls, gait velocity, turn time, turn number of steps, and down 3 stairs **Model** 3 (recurrent falls): Multiple falls, gait velocity, turn time, and turn number of steps **Model** 4 (recurrent falls): Multiple falls, quiet standing, maximal leaning, sway area, and medial-lateral excursion **Model** 5 (recurrent falls): Multiple falls, quiet standing, maximal leaning	**Model** 2: AUC: no information Calibration: no information Extracted from figure 2: SN: 55%; SP: 55% **Model** 3: AUC: no information Calibration: no information Extracted from figure 2: SN: 55%; SP: 52% **Model** 4: AUC: no information Calibration: no information Extracted from figure 2: SN: 78%; SP: 55% **Model** 5: AUC: no information Calibration: no information Extracted from figure 2: SN: 68%; SP: 55%
Bongue et al. [15], 2011, France, Development study	n = 1,759 Age, mean (SD): 70.7 (4.6) years Female: 51% Prior falls: 26%	Any falls (563; 32%) Follow-up: 12 months	Cox regression No information on model validation	**Model** 1 (time to any falls): Regression table (coefficient): baseline hazard: no information; women 0.506; living alone: in couple: 0, family: 0.438, alone: 0.315; self-reported osteoarthritis: 0.22; history of falls - 1 year: 0 falls: 0, 1 fall: 0.616, 2 falls: 0.907, 3 or more falls: 1.42; psychoactive drug use: 0.217; balance impairment: 0.270 Scoring rule (points): women (2); living alone (1); self-reported osteoarthritis (1); history of falls - 1 year: 1 fall (2), 2 falls (4), 3 or more falls (6); psychoactive drug use (1); balance impairment (1) Cut-off: 7 Low risk: Score: 0-3; frequencies: 55.3; OR: 1 Moderate risk: Score: 4-6; frequencies: 34.9; OR 2.4 (2.2-3.4) High risk: Score: 7-12; frequencies: 9.8; OR: 7.8 (5.5-11.1)	**Model** 1: AUC (CI): 0.70 (0.67-0.73) Calibration: no information Youden index = 3, for this: SN: 70.2% SP: 60.3% PPV: 45.5% NPV: 81.1% Evolution of PPV and NPV cut-off = 7, for this: SN: 19.2% SP: 96.5% PPV: 72% NPV: 72.7%
Viccaro et al. [16], 2011, USA,	n = 492	First time falls (83; 19.5%)	Logistic regression	**Model** 1 (first time fall):	**Model** 1: AUC: 0.60

Development study	Age, mean (SD): 74 (5.7) years Of the 457 with complete follow-up (except n = 18 who died during follow-up): female: 43.5% Prior falls: 29.7%	Any falls (155; 36.5%) Recurrent falls (58; 13.9%) Follow-up: 12 months	No information on model validation	Timed Up & Go test, 4 m gait speed test, age, and fall history **Model** 2 (any fall): Timed Up & Go test, 4 m gait speed test, age, and fall history **Model** 3 (recurrent falls): Timed Up & Go test, 4 m gait speed test, age, and fall history	Calibration: no information **Model** 2: AUC: 0.729 Calibration: no information **Model** 3: AUC: 0.786 Calibration: no information
Yamashita et al. [17], 2012, USA, Development study	n = 9,661 Age, mean (SD): 74.2 (7.16) years Of the 9,592 included in the analyses: female: 57.8% Prior falls: 31%	Any falls (3,299; 34%) Follow-up: 24 months	Logistic Tree with Unbiased Selection (LOTUS)/ Logistic Regression Tree Method Cross-validation (10 subsets)	**Model** 1 (any falls): Fall history, age, difficulty with knees, activities of daily living, cognitive impairment, self-rated health, instrumental activities of daily living, prescription drugs, and stroke	**Model** 1: AUC: 0.71 Calibration: no information
Weiss et al. [18], 2013, Israel, Development study	n = 71 Age, mean (SD): 78.36 (4.71) years Female: 65% Prior falls: 45%	Recurrent falls (12; 16.9%) Follow-up: 6 months	Logistic regression No information on model validation	**Model** 1 (recurrent falls): Four Square Step Test, total activity duration (Accelerometer), anterior-posterior acceleration range (Accelerometer), anterior-posterior width (Accelerometer), and age	**Model** 1: AUC: no information Calibration: no information SN: 75% SP: 100% "94.7% of the subjects were successfully identified as future fallers and non-fallers"
Hnizdo et al. [19], 2013, USA, Validation	n = 113 Age, mean: 79.8 years Female: 34.6% Prior falls: 49.5%	Any falls (33; 29.2%) Follow-up: participants were followed until discharged from home health services	Validation study	**Model** 1 (any falls): Age, fall history, elimination problems, high risk medications, use of patient care equipment, limited mobility, and altered cognition	**Model** 1: AUC (95% CI): 0.66 (0.55-0.78) Calibration: no information Cut-off: 14 points SN: 72.5% SP: 52.2% PPV: 39.6% NPV: 81.4%
de Vries et al. [20], 2013, The Netherlands, Development study	n = 1,509 Age, median (range): 75.6 (64.8-88.8) years Female: 51.8% Prior falls: 32.2%	Recurrent falls, ≥ 2 falls (174; 11.5%) Recurrent falls, ≥ 3 falls (91; 6%) Any falls	Cox regression Logistic regression No information on model validation	**Model** 1 (time to second fall): Low mastery, depression, urinary incontinence, hearing impairment, low physical activity, low visual acuity, body mass index ≤23, low peak flow, Mini-Mental State Examination ≤ 24 **Model** 2 (any falls): Low mastery, depression, urinary incontinence, hearing impairment, low physical activity, low	**Model** 1: AUC:0.58 (0.53-0.62) Calibration: no information **Model** 2: AUC: 0.51 (0.346-0.56) Calibration: no information **Model** 3:

		(468; 31.0%) Follow-up: 12 months		visual acuity, body mass index ≤23, low peak flow, Mini-Mental State Examination ≤ 24 **Model** 3 (recurrent falls, ≥ 2 falls): Low mastery, depression, urinary incontinence, hearing impairment, low physical activity, low visual acuity, body mass index ≤23, low peak flow, Mini-Mental State Examination ≤ 24 **Model** 4 (recurrent falls, ≥ 3 falls): Low mastery, depression, urinary incontinence, hearing impairment, low physical activity, low visual acuity, body mass index ≤23, low peak flow, Mini-Mental State Examination ≤ 24	AUC: 0.50 (0.42-0.57) Calibration: no information **Model** 4: AUC: 0.49 (0.39-0.59) Calibration: no information
Muhaidat et al. [21], 2014, United Kingdom, Development study	n = 66 Non-fallers: Age, mean (SD): 75 (11.5) years Fallers: Age, mean (SD): 82 (12) years Female: 66% Prior falls: 45%	Any fall (13; 19.7%) Follow-up: 6 months	Random Forrest Classification Training set 67% of the sample Test set: 33% of the sample	**Model** 1 (any falls): Table of predictors with corresponding Mean Decrease in Accuracy, and Mean Decrease in Gini: time required to complete triple task, time required avoiding a moving obstacle and cup, time required for TUG and cup, time required for single-task avoiding a moving obstacle, absolute difference in time between single-task TUG and dual-task TUG	**Model** 1: AUC: no information Calibration: no information Out-of-bag error rate: 27.4% Correct classification: 72.6%
Gadkaree et al. [22], 2015, USA, Development study	n = 7,609 Age groups, % (CI): - 65-69: 27.9% (27.0-29.0) - 70-74: 25.0% (24.1-25.8) - 75-79: 19.1% (18.2-19.9) - 80-84: 14.7% (14.0-15.4) - 85-89: 9.1% (8.5-9.8) - 90+: 4.3% (3.8-4.7) Female: 56.6% Prior falls: 30.5%	Any falls (2,028; 26.7%) Recurrent falls (957; 12.6%) Follow-up: 12 months	Logistic regression Split-sample validation (random split; 66.6%/33.3%) Cross-validation (no information on subsets)	**Model** 1 (any falls): Age, gender, and race **Model** 2 (recurrent falls): Age, gender, and race **Model** 3 (any falls): y = -1.44 + ((Age 70-74 years)* -0.33) + ((Age 75-59 years)*0.07) + ((Age 80-84 years)*0.17) + ((Age 85-89 years)*0.37) + ((Age 90+ years)*0.26) + Female*0.12 + (Black ethnicity * -0.27) + (Other ethnicity * -0.52) + (Hispanic ethnicity * 0.07) + Self-reported balance problems*0.69 + Fall history*1.15 **Model** 4 (recurrent falls)	**Model** 1: AUC (95% CI): 0.57 (0.54-0.60) Calibration: no information **Model** 2: AUC (95% CI): 0.59 (0.56-0.61) Calibration: no information **Model** 3: AUC (95% CI): 0.69 (0.67-0.71) Calibration: no information Performance in validation set: AUC (95% CI): 0.70 (0.67-0.73) **Model** 4: AUC (95% CI): 0.77 (0.74-0.79)

				y = 2.67 + ((Age 70-74 years)* -0.66) + ((Age 75-59 years)*-0.08) + ((Age 80-84 years)*0.11) + ((Age 85-89 years)*0.49) + ((Age 90+ years)*0.47) + Female*-0.22 + (Black ethnicity * -0.27) + (Other ethnicity * -0.99) + (Hispanic ethnicity * 0.02) + Self-reported balance problems*1.11 + Fall history*1.46 **Model** 5 (any falls): Age, gender, race, self-reported balance problems, history of falls, heart attack, heart disease, stroke, hypertension, diabetes, osteoporosis, vision impairment, and hearing impairment **Model** 6 (recurrent falls): Age, gender, race, self-reported balance problems, history of falls, heart attack, heart disease, stroke, hypertension, diabetes, osteoporosis, vision impairment, and hearing impairment **Model** 7 (any falls): Age, gender, race, self-reported balance problems, history of falls, heart attack, heart disease, stroke, hypertension, diabetes, osteoporosis, vision impairment, hearing impairment, and Short Physical Performance Battery **Model** 8 (recurrent falls): Age, gender, race, self-reported balance problems, history of falls, heart attack, heart disease, stroke, hypertension, diabetes, osteoporosis, vision impairment, hearing impairment, and Short Physical Performance Battery	Calibration: no information Performance in validation set: AUC (95% CI): 0.76 (0.73-0.80) **Model** 5: AUC (95% CI): 0.71 (0.69-0.73) Calibration: no information **Model** 6: AUC (95% CI): 0.78 (0.76-0.81) Calibration: no information **Model** 7: AUC (95% CI): 0.72 (0.70-0.73) Calibration: no information **Model** 8: AUC (95% CI): 0.79 (0.76-0.81) Calibration: no information
Cawthon et al. [23], 2015, USA, Development study	n = 5,994 Age, mean: 74 years (based on other studies on the same cohort)	Recurrent falls (694; 11.6%) Follow-up: 12 months	Logistic regression No information on model validation	**Model** 1 (recurrent falls): Age and Baumgartner Sarcopenia Definition **Model** 2 (recurrent falls): Age and Newman Sarcopenia Definition	**Model** 1: Change in AUC compared to age alone (AUC: 0.577): 0.000 (-0.002; 0.003) Calibration: "We did not generate calibration plots for these

	Female: 0% Prior falls: 21% (based on other studies on the same cohort)			**Model** 3 (recurrent falls): Age and IWG Sarcopenia Definition **Model** 4 (recurrent falls): Age and EWGSOP Sarcopenia Definition **Model** 5 (recurrent falls): Age and FNIH Definition#1 **Model** 6 (recurrent falls): Age and FNIH Definition#2	analyses, just the discrimination and the C statistic information" (author response) NRI events: 0.12 (0.08, 0.16) NRI non-events: -0.12 (-0.14, -0.11) **Model** 2: Change in AUC compared to age alone (AUC: 0.577): 0.001 (-0.002; 0.003) Calibration: no information NRI events: 0.07 (0.04, 0.11) NRI non-events: -0.08 (-0.09, -0.06) **Model** 3: Change in AUC compared to age alone (AUC: 0.577): 0.010 (0.002; 0.018) Calibration: no information NRI events: -0.33 (-0.38, -0.28) NRI non-events: 0.34 (0.32, 0.35) **Model** 4: Change in AUC compared to age alone (AUC: 0.577): 0.009 (0.002; 0.015) Calibration: no information NRI events: -0.33 (-0.38, -0.28) NRI non-events: 0.35 (0.34, 0.36) **Model** 5: Change in AUC compared to age alone (AUC: 0.577): 0.004 (-0.001; 0.008) Calibration: no information NRI events: -0.11 (-0.14, -0.08) NRI non-events: 0.07 (0.06, 0.08) **Model** 6:

					Change in AUC compared to age alone (AUC: 0.577): 0.001 (-0.001; 0.003) Calibration: no information NRI events: -0.05(-0.06, -0.03) NRI non-events: 0.03(0.02, 0.03)
Palumbo et al. [24], 2016, Italy, Germany, Ireland, and England, Validation	ActiFE: n = 1,416 ELSA: n = 3,303 InCHIANTI: n = 892 TILDA: n = 2,101 Age, mean (SD): ActiFE: 75.7 (6.76) years ELSA: 74.56 (7.31) years InCHIANTI: 73.78 (6.62) years TILDA: 72.79 (5.22) years Female: ActiFE: 56.8% ELSA: 56.7% InCHIANTI: 56.2% TILDA: 53.5% Prior falls: ActiFE: 36.1% ELSA: 22.7% InCHIANTI: 20.8% TILDA: 22.8%	Any falls ActiFE (466; 32.9%) ELSA (730; 22.1% 1 years adjusted) InCHIANTI (203; 22.8%) TILDA (569; 27.1% 2 years adjusted) Follow-up: ActiFE: 12 months ELSA: 2 years InCHIANTI: 1 year TILDA: 2 years	Validation study	**Model** 1 (any falls): Age, cognitive impairment, depression, diabetes, comorbidity, dizziness and vertigo, fear of falling, female sex, gait problems, hearing impairment, history of falls, history of stroke, instrumental disability, living alone, number of medications, pain, Parkinson's disease, physical activity limitation, physical disability, poor self-perceived health status, rheumatic disease, urinary incontinence, use of antiepileptics, use of antihypertensives, use of sedatives, vision impairment, and walking aid use	**Model** 1: ActiFE: AUC (95% CI): 0.562 (0.530 - 0.594) ELSA: AUC (95% CI): 0.699 (0.680 - 0.718) InCHIANTI: AUC (95% CI): 0.636 (0.594 - 0.681) TILDA: AUC (95% CI): 0.685 (0.660 - 0.709) Calibration: calibration plots were displayed for all four cohorts. For ActiFE and InCHIANTI, participants with low (high) risk scores, experienced more (respectively, less) falls than expected. For ELSA and TILDA, the model overestimated the risk consistently across strata
Rodriguez-Molinero et al. [25], 2017, Spain, Development study	n = 772 Of participants completing the first follow-up period, age, median (SD): 80.7 (0.1) years Of participants completing the first follow-up period, female: 62.5% Prior falls: 26.4%	Recurrent falls (43; 9.9%) Follow-up: 12 months	No regression analyses were performed. Sensitivity, specificity and area under the ROC curve (AUC) were calculated as well as the Odds Ratio (OR) and Relative Risk (RR) associated to positive responses	**Model** 1(recurrent falls): Score chart (range 1-6) on the questions: - Have you ever fallen in the last 6 months? - What is the probability that you fall in the next few months?	**Model** 1: AUC (95% CI): 0.74 (0.66-0.82) Calibration: after contacting study authors, a calibration plot was provided showing acceptable calibration. Calibration slopes were not considered. Cut-off: 3 points SN (95% CI): 70% (56%-84%) SP (95% CI): 72% (68%-76%)

			No information on model validation		
Lohman et al. [26], 2017, USA, Development study	n = 7,609 Age groups, n (%): 65-69 years: 2,099 (28.4%) 70-74 years: 1,863 (25.2%) 75-79 years: 1,427 (19.3%) 80-84 years: 1,079 (14.6%) 85-89 years: 636 (8.6%) 90+ years: 288 (3.9%) Female: 56.4% Prior falls: no information	Any falls (3,903; 51.3%) Recurrent falls (2,181; 28.7%) Follow-up: 48 months	Logistic regression No information on model validation	**Model** 1 (any falls): STEADI algorithm: - Low risk, all present: no falls in past year, no worrying about falling, no unsafe/unsteady feeling while walking - Moderate risk, all present: yes, to one of the above-mentioned questions the low risk group, >4 chair stands in 30 sec., completion of all balance stages in 4 stage balance test. If NO to one of tests then both succeeding questions need to be answered as follows: no multiple falls in the past year, and no previous hip fracture since the age of 50 - High risk, all present: the same as in the moderate risk group except one of the succeeding questions are answered as follows: yes, to multiple falls in the past year or yes to previous hip fracture since the age of 50 **Model** 2 (any falls): Covariates: age, race, gender, education, living alone, smokings status, body mass index, vision impairment, hearing impairment, medical burden, functional Impairment, and frailty **Model** 3 (any falls): Model 1 and 2 combined	**Model** 1: AUC: 0.641 ("No CI was calculated" – author response) Calibration: no information SN: 65% SP: 65% PPV: 62% NPV 68% **Model** 2: AUC: 0.575 Calibration: no information **Model** 3: AUC: Calibration: no information
Kim et al. [27], 2017, USA, Development study + Validation study	Development: n = 5,593 (3,960 at follow-up) Validation: n = 4,424 (3,273 at follow-up) Age, median (IQR): Development: 77 (71, 83) Validation: 78 (71, 83) Female: Development: 58.4% Validation: 57.4% Prior falls: no information	Recurrent falls - Development: (834; 14.9%) - Validation: (514; 11.6%) Follow-up: No exact length of follow-up was reported. However, they reported that they wanted to predict the outcomes in the following year from baseline	Lasso regression model Bootstrap validation	**Model** 1 (recurrent falls - development): Age, sex, combined comorbidity index, 52 International Classification of Diseases 9-codes, 25 Current Procedural Terminology codes, and 16 Healthcare Common Procedure Coding System level II codes **Model** 2 (recurrent falls - validation): Age, sex, combined comorbidity index, 52 International Classification of Diseases 9-codes, 25 Current Procedural Terminology codes, and 16 Healthcare Common Procedure Coding System level II codes	**Model** 1: C-statistic: 0.62-0.66 Calibration: no information **Model** 2: C-statistic: consistent with C-statistic in Development study sample Calibration: no information

Palumbo et al. [28], 2018, Italy, Development study	n = 541 Age, mean (SD): 82.4 (6.5) years Of the 438 participants with a complete data set, female: 60.7% Prior falls: 27%	Recurrent falls (34; 6.3%) Any falls (87; 16.1%) Follow-up: 12 months	No regression analysis was performed. The predictive accuracy was quantified from TP, TN, FP and FN in terms of SN, SP, PPV, NPV, and accuracy No information on model validation	**Model** 1 (any fall): A table with classification measures for the model with 3 different cut-off values for the TUG-test. Predictors were two or more falls in the past 12 months, presents with acute fall, difficulty with walking or balance, single fall in the past 12 months, and Timed up and go test (cut-off: >12 s, >13.5s, and >15s) **Model** 2 (any fall): A table with classification measures for the model with 2 different cut-off values for the SPPB. Predictors were two or more falls in the past 12 months, presents with acute fall, difficulty with walking or balance, single fall in the past 12 months, and Short Physical Performance Battery (cut-off: < 9, and < 11 point) **Model** 3 (any falls): A table with classification measures for the model with 2 different cut-off values for the 7m gait speed test. Predictors were two or more falls in the past 12 months, presents with acute fall, difficulty with walking or balance, single fall in the past 12 months, and 7m gait speed test (cut-off: <0.8 m/s, and < 1m/s) **Model** 4 (recurrent falls): A table with classification measures for the model with 3 different cut-off values for the TUG-test. Predictors were two or more falls in the past 12 months, presents with acute fall, difficulty with walking or balance, single fall in the past 12 months, and Timed up and go test (cut-off: >12 s, >13.5s, and >15s) **Model** 5 (recurrent falls): A table with classification measures for the model with 2 different cut-off values for the SPPB. Predictors were two or more falls in the past 12 months, presents with acute fall, difficulty with walking or balance, single fall in the past 12 months, and Short Physical Performance Battery (cut-off: < 9, and < 11 point)	**Model** 1: AUC: no information Calibration: no information TUG > 12s: SN: 36.5% (22.3%-54.5%) SP: 82.5% (76.9%-87.1%) PPV: 25.5% (16.8%-37.6%) NPV: 88.8% (83%-93.6%) Accuracy: 76% (70.2%-81.4%) TUG > 13.5s: SN: 35.8% (23.2%-52.7%) SP: 84% (79.3%-88.4%) PPV: 26.9% (17.3%-38.8%) NPV: 88.8% (83.9%-93.7%) Accuracy: 77.2% (72.4%-82.3%) TUG > 15s: SN: 35.1% (22.7%-52.6%) SP: 84.1% (79.3%-88.4%) PPV: 26.7% (17.5%-38.7%) NPV: 88.7% (83.2%-93.1%) Accuracy: 77.2% (71.7%-82.4%) **Model** 2: AUC: no information Calibration: no information SPPB < 9: SN: 37.2% (24.1%-54.1%) SP: 83.4% (78.7%-87.7%) PPV: 27% (17.8%-37.6%) NPV: 89% (83.3%-94%) Accuracy: 76.9% (71%-81.8%) SPPB < 11: SN: 43.3% (28.4%-62.7%) SP: 79% (72.7%-84.5%) PPV: 25.4% (16.4%-35.8%) NPV: 89.4% (83.9%-94.3%) Accuracy: 74% (67.8%-79.9%) **Model** 3: AUC: no information Calibration: no information

				Model 6 (recurrent falls): A table with classification measures for the model with 2 different cut-off values for the 7m gait speed test. Predictors were two or more falls in the past 12 months, presents with acute fall, difficulty with walking or balance, single fall in the past 12 months, and 7m gait speed test (cut-off: <0.8 m/s, and < 1m/s)	Gait speed < 0.8 m/s: SN: 35.1% (22.6%-52.5%) SP: 84.3% (78.8%-88.6%) PPV: 26.9% (17.7%-39.1%) NPV: 88.8% (82.9%-93.4%) Accuracy: 77.4% (71%-82.5%) Gait speed < 1 m/s: SN: 35.8% (22.4%-54.4%) SP: 82.4% (76.9%-87.3%) PPV: 25.1% (15.9%-36.5%) NPV: 88.6% (83%-93.3%) Accuracy: 75.8% (69.8%-81.5%) **Model** 4: AUC: no information Calibration: no information TUG > 12 s: SN: 56.2% (32.2%-92.8%) SP: 82.1% (76.9%-86.6%) PPV: 16.8% (8.9%-27.8%) NPV: 96.7% (92.9%-99.7%) Accuracy: 80.5% (75%-85.3%) TUG > 13.5s SN 56.2% (27.6%-89.8%) SP: 83.6% (79.4%-87.6%) PPV: 18.1% (9.7%-29.2%) NPV: 96.7% (92.3%-99.6%) Accuracy: 81.9% (76.9%-86.4%) TUG > 15 s SN: 56.2% (30.3%-92.6%) SP: 83.8% (79.2%-87.7%) PPV: 18.3% (10%-28.6%) NPV: 96.7% (93.1%-99.7%) Accuracy: 82.1% (76.9%-86.8%) **Model** 5: AUC: no information Calibration: no information SPPB < 9: SN: 56.2% (32.1%-93.2%)

					SP: 82.9% (78.1%-87%) PPV: 17.5% (9.3%-28.4%) NPV: 96.7% (93%-99.7%) Accuracy: 81.3% (76%-85.6%) SPPB < 11: SN: 59% (32.3%-97.4%) SP: 78.1% (72.4%-83.3%) PPV: 14.8% (8.1%-24.3%) NPV: 96.7% (92.7%-99.9%) Accuracy: 76.9% (71%-82.6%) **Model** 6: AUC: no information Calibration: no information Gait speed < 0.8 m/s: SN: 56.2% (30.6%-91.7%) SP: 84% (79.3%-88.2%) PPV: 18.4% (9.9%-29.9%) NPV: 96.7% (93.1%-99.7%) Accuracy: 82.3% (77.2%-87.2%) Gait speed < 1 m/s: SN: 56.2% (30.8%-92%) SP: 82.1% (77.2%-86.5%) PPV: 16.8% (8.9%-27.4%) NPV: 96.7% (92.9%-99.6%) Accuracy: 80.5% (74.9%-85.3%)
Singh et al. [29], 2019, Malaysia, Development study	n = 325 Age, mean (SD): 67.55 (5.5) years Of the n = 305 analysed, female: 56.1% Prior falls: 16.7%	Any falls (81; 24.9%) Follow-up: 6 months	Logistic regression No information on model validation	**Model** 1 (any falls): constant: -5.03, age: -0.003, gender: 0.19, medication: -0.24, primary education: -0.27, secondary education: -0.85, history of falls: 0.67, Walk While Talking Test: 0.68, gait speed: 0.25, instrumental activities of daily living: -0.01, Timed up and go test: 0.14, and Physiological Profile Assessment: 1.16 **Model** 2 (any falls): constant: -5.06, age: 0.05, gender: 0.46, medication: -0.14, primary education: 0.07, secondary education: 0.85, history of falls: 0.12, Walk While Talking Test: 0.23, gait speed: -	**Model** 1: Cox-Snell R^2: 0.21 Nagelkerke R^2: 0.31 AUC: no information Calibration: "Hosmer-Lemeshow test result confirmed that the model was a good fit for the data $\chi 2(df = 8, N = 305) = 10.80, P = .21$" Accuracy: 76.6% **Model** 2: Cox-Snell R^2: 0.07 Nagelkerke R^2: 0.95 AUC: no information Calibration: "Hosmer-Lemeshow test results confirmed that the

				0.07, instrumental activities of daily living: -0.03, and Timed up and go test: 0.16	model was a good fit for the data $\chi 2$ (df = 8, N =305) = 4.77, P = 0.78" Accuracy: 74.1%
Gillain et al. [30], 2019, Belgium, Development study	n = 105 Age, mean (SD): 71.3 (5.4) years Age, range: 65-89 years Of the 96 analysed, female: 50% Prior falls: 0%	First time falls (35; 33.3%) Follow-up: 24 months	Classification tree Split-sample validation (no information on allocation) Cross-validation (10 subsets)	**Model** 1 (first time falls): Classification tree: symmetry dual task walking condition cost, fast walking condition stride length, stiffness, comfortable walking condition mean minimum toe clearance, dual task walking condition coefficient of variation of minimum toe clearance cost, fast walking condition variance of minimum toe clearance values, fast walking condition mean minimum toe clearance value, dual task walking condition delta1 minimum toe clearance, and gender	**Model** 1: AUC: 0.84 Calibration: no information SN: 80% SP: 87% PPV: 78% NPV: 88%

Note: AUC = Area Under the Curve; Any falls = both single a CI = confidence interval; COP = centre of pressure; FN = False negative; FP = False positive; kg = kilograms; LOS = limits of stability; +LR = positive likelihood ratio; -LR = negative likelihood ratio; PPV = positive predictive value; N = no; NPV = negative predictive value; n = number; SD = standard deviation; SE = standard error; SN = sensitivity; SP = specificity; TN = True negative; TP = True positive; Y = yes; % = percentage proportion

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Appendix 10: extracted data

See separate PDF file: “Appendix 10”.